Impact of climate change on hydrological conditions in a tropical West African catchment using an ensemble of climate simulations

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Abstract. This study evaluates climate change impacts on water resources using an ensemble of six Regional Climate Models (RCMs)-Global Climate Models (GCMs) in the Dano catchment (Burkina Faso). The applied climate datasets were performed in the framework of the COordinated Regional climate Downscaling Experiment (CORDEX-Africa) project.

After evaluation of the historical runs of the climate models ensemble, a statistical bias correction (*Empirical Quantile Mapping*) was applied to daily precipitation. Temperature and bias corrected precipitation data from the ensemble of RCMs-GCMs was then used as input for the Water flow and balance Simulation Model (WaSiM) to simulate water balance components.

The mean hydrological and climate variables for two periods (1971-2000 and 2021-2050) were compared to assess the potential impact of climate change on water resources up to the middle of the twenty-first century under two greenhouse gas concentration scenarios, the Representative Concentration Pathways (RCPs) 4.5 and 8.5. The results indicate: (i) a clear signal of temperature increase of about 0.1 to 2.6 °C for all members of the RCMs-GCMs ensemble; (ii) high uncertainty about how the catchment precipitation will evolve over the period 2021-2050; (iii) the applied bias correction method only affected the magnitude of climate change signal (iv) individual climate models results lead to opposite discharge change signals; (iv) the results for the RCMs-GCMs ensemble are too uncertain to give any clear direction for future hydrological development. Therefore, potential increase and decrease of future discharge has to be considered in climate change adaptation strategies in the catchment. The results further underline on the one hand the need for a larger ensemble of projections to properly estimate the impacts of climate change on water resources in the catchment and on the other hand the high uncertainty associated with climate projections for the West African region. A water-energy budget analysis provides further insight into the behavior of the catchment.

Keywords: Hydrological modeling, RCP, bias correction, West Africa, Ecohydrological analysis.

1. Introduction

Development of adaptation strategies to deal with potential impacts of climate change on hydrological systems is a considerable challenge for water resources management (Muerth et al., 2013; Piani et al., 2010). Besides being highly exposed to climate change, the West African region presents a low adaptive capacity (IPCC, 2014). Projections for the late 21st century suggest severe consequences of climate change on water resources for the region. This includes an increased risk of water stress and flood (Sylla et al., 2015; Oyerinde et al., 2014), and significant change in river discharge (Aich et al., 2014; Ardoin-Bardin et al., 2009; Mbaye et al., 2015).

Rising temperatures, commonly acknowledged by regional climate models (RCMs) and global climate models (GCMs), are expected to intensify the hydrological cycle due to an increased water holding capacity of the atmosphere, leading to an increased amount of renewable fresh water resources (Piani et al., 2010). Another consequence of temperature increase ascertained by Piani et al. (2010) for some regions, is the decrease in precipitation associated with the intensification of the seasonal cycle and the frequency of extreme events. These opposite trends imply that high uncertainties are associated with predicted rising temperatures' impact on the hydrological cycle for some regions (Salack et al., 2015).

Confidence in RCMs and GCMs over West Africa relies on their ability to simulate the West African monsoon (WAM) precipitation (Klein et al., 2015). However, simulating the WAM remains challenging for both RCMs and GCMs (Cook, 2008; Druyan et al., 2009; Paeth et al., 2011; Ruti et al., 2011), as each RCM and GCM produces a version of the WAM, but with some distortion of structure and/or timing. Some GCMs (e.g. CSIRO, GISS_ER , ECHAM5, CCSM) do not generate the WAM at all (Cook and Vizy, 2006). Part of this divergence is related to: (i) imperfect characterization of tropical precipitation systems; (ii) uncertain future greenhouse gas forcing; (iii) scarcity of observations over West Africa; and (iv) natural climate variability (Cook and Vizy, 2006; Foley, 2010).The hydrological climate change signal is therefore unclear for the region. Several authors (Kasei, 2009; Paeth et al., 2011; Salack et al., 2015) observed diverging precipitation signals among models. Moreover, several models fail to accurately reproduce the historical rainfall onset, maxima, pattern, and amount of the region (Nikulin et al., 2012; Ardoin-Bardin et al., 2009).

Despite significant advances, outputs of GCMs and RCMs are still characterized by biases that challenge their direct use in climate change impact assessment (Ehret et al., 2012). Indeed, unless the precipitation from climate models are bias corrected, results from hydrological simulations are often reported to be unrealistic and may lead to incorrect impact assessments (Johnson and Sharma, 2015; Teutschbein and Seibert, 2012; Ahmed et al., 2013). However, correction of climate model based simulation results does not ensure physical consistency (Muerth et al., 2013) and may affect the signal of climate change for specific regions as reported by Hagemann et al. (2011). Consequently, simulated hydrological variables using bias corrected data need to be explored in climate change impact assessment.

There is essential consensus on the necessity of performing multi (climate)-model assessments to estimate the response of the West African climate to global change (Sylla et al., 2015). Accordingly, several studies (e.g. Chen et al., 2013; Zhang et al., 2011) emphasize the importance of using multiple climate models to account for uncertainty when assessing climate change impacts on water resources. Taking advantage of the results of the COordinated Regional climate Downscaling Experiment (CORDEX-Africa) project, this study evaluates potential climate change impacts on water resources using an ensemble of six RCMs-GCMs in the Dano catchment in Burkina Faso. The catchment experiences seasonally limited water availability, and like other catchments of the region, it has experienced the severe droughts of the 1970s (Kasei et al., 2009) which resulted in a decline of discharge in many West African catchments.

A few studies have already investigated the impacts of projected climate change on water resources in West Africa (see Roudier et al. 2014 for a review). Many of these studies have used an approach based on hydrological models driven by a single RCM or GCM data set (e.g. Mbaye et al., 2015; Cornelissen et al., 2013; Bossa et al., 2014; Bossa et al., 2012). Therefore, uncertainty related to the choice of the climate model was not explicitly evaluated. However, other studies have used multi-climate model data sets (Kasei, 2009; Ruelland et al., 2012, Aich et al. 2016); most of these studies have resulted in a diverging projected hydrological change signal. Climate model outputs have often been bias corrected to fit the historical climate variables and then used as input for hydrological models but few have investigated the necessity of performing such corrections in detecting the signal of future climate change impacts on water resources.

The current study aims to investigate the future climate change impacts on the hydrology of the Dano catchment in Burkina Faso, thus contributing to the management of water resources in the region. Besides the small scale of the catchment that implies addressing scale issues, the novelty of the study includes a water-energy budget analysis. Specifically, it has the following objectives: (i) evaluate the historical runs of six RCMs-GCMs at the catchment scale; (ii) analyze the climate change signal for the future period of 2021-2050 compared to the reference period of 1971-2000; (iii) evaluate the ability of the climate models to reproduce the historical discharge, (iii) assess the impacts of climate change on the hydrology of the catchment by the middle of the 21st (iv) perform an ecohydrological analysis of the catchment under climate change.

2. Materials and methods

2.1. Study area

The study was carried out in Dano catchment covering a total area of 195 km^2 in the Ioba province of Southwestern Burkina Faso (Fig. 1). The catchment is one of the study areas of the WASCAL project (West African Science Service Center on Climate Change and Adapted Land Use, www.wascal.org); whose main target is to increase resilience of human and environmental systems to climate change.

The major land uses in the catchment include shifting cultivation which accounts for one third of the catchment area; natural vegetation albeit converted into agricultural and fallow lands form part of Sudanian region characterized by wooded, scrubby savannah and abundant annual grasses. Sorghum (Sorghum bicolor), millet (*Pennisetum glaucum*), cotton (*Gossypium hirsutum*), maize (*Zea mays*), cowpeas (*Vigna unguiculata*) and groundnut (*Arachidis hypogaea*) are the major crops cultivated in the catchment.

The catchment is characterized by a flat landscape with a mean slope of 2.9 % and mean altitude of 295 m above sea level. According to Schmengler (2011), mean annual temperature of 28.6 ^{0}C was recorded while mean annual rainfall ranged from 800 mm – 1200 m for the period of 1951- 2005. The catchment receives monsoonal rains with a dry season occurring in the months of November to April while the wet season being experienced in the months of July to September. This kind of rainfall pattern limits water availability especially in the dry season hence communities in the catchment are vulnerable to water scarcity since they heavily rely on surface water.

Plinthosol characterized by a plinthite subsurface layer in the upper first meter of the soil profile accounts for 73.1 % of the soil types in the catchment, other soil types found within the catchment include *gleysol*, *cambisol*, *lixisol*, *leptosol* and *stagnosol* (WRB, 2006).

2.2. Climate data

Observed mean daily temperature and daily precipitation used in the study were collected from the national meteorological service of Burkina Faso (DGM). The dataset covers the reference period of 1971-2000. Although the national observation network includes several rainfall gauges and synoptic stations, solely the data of the Dano station were used as it is located in the study area.

An ensemble of six RCM-GCM datasets is exploited in the study (Table 1). The RCM-GCM simulations were performed in the framework of the CORDEX-Africa project. The datasets were produced by three RCM groups (CCLM: Climate Limited-area Modelling Community, Germany; RACMO22: Royal Netherlands Meteorological Institute, Netherlands; HIRHAM5: Alfred Wegener Institute, Germany) using the boundary conditions of four GCMs (CNRM-CM5, EC-EARTH, ESM-LR, NorESM-M). Each dataset consists of historical runs and projections based on the emission scenarios RCP4.5 and RCP8.5 (Moss et al., 2010). The retrieved data (precipitation and temperature) range form 1971-2000 for the historical runs and 2021-2050 for the RCPs.

An extent of 9 nodes (3x3, which is the RCM models resolution degraded by a factor of 3) of the African CORDEX domain, surrounding the catchment, was delineated to simulate the catchment's climate (Fig. 1 B). The areal mean of the 9 nodes was used to evaluate the simulated precipitation against the observations at the Dano station (the reference station). The climate variables (historical and projected) of the extent of 9 nodes were used as inputs for the hydrological simulation model as well.

Due to the discrepancy between the RCM-GCM data resolution (0.44°, about 50 km * 50 km) and the hydrological modeling domain (about 18 km * 11 km) the data of each node were separately used as climate input for the hydrological simulation model. Therefore, for each period (historical and projected scenarios) 9 simulations corresponding to the 9 nodes are performed per RCM-GCM. Monthly water balance for each RCM-GCM is then calculated as arithmetic mean.

2.3. Bias correction of precipitation data

The RCMs-GCMs ensemble was evaluated to get an estimate of the historical simulated variables for the catchment by comparing RCMs-GCMs based simulations of historical climate variables to the observations provided by the National Meteorological Service (DGM). As presented in section 3.1, whereas temperature simulated by the models ensemble enveloped the observed temperature with moderate deviation, precipitation simulated by individual RCM-GCM exhibited biases such as overestimation of annual precipitation as well as misrepresentation of the timing of the rainy season. A precipitation bias correction was therefore applied to the six RCMs-GCMs following the non-parametric quantile mapping using the empirical quantiles method (Gudmundsson et al.; 2012). For each member, transfer functions (*TFs*) were derived using observed and modeled precipitation for the period of 1971-2000; afterwards the transfer functions were applied to the projected climate scenarios (period 2021-2050).

However, a consistent application of bias correction is subject to numerous hypotheses that need to be fulfilled, at the risk of altering the climate change signal (Muerth et al., 2013; Ehret et al., 2012; Hagemann et al., 2011). This includes the hypotheses of reliability, effectiveness, time invariance or stationarity, completeness etc. (a complete discussion on these hypotheses is provided by Ehret et al., 2012). Precipitation in the Dano region is characterized by a strong decadal variability and a non-stationary annual behavior (Oyerinde et al., 2014; Karambiri et al., 2011; Waongo, 2015), which implies that a *TF* derived from a short period (e.g. a decade) does not fulfill the time invariant hypothesis. Similarly, a *TF* derived from a short period precludes the hypothesis of completeness and is likely not to be suitable for application to a period that does not overlap the derivation period as *TFs* are likely to change from a period to another (Piani et al., 2010).

A cross-validation approach (e.g. Lafon et al., 2013; Teutschbein and Seibert, 2013) using the periods of 1971- 1990 and 1991-2000 for calibration and verification respectively, showed that for the climate model ensemble biases in precipitation are in general reduced by the bias correction method (Fig. 2). However, due to mentioned decadal signal that characterizes precipitation variability in the region; considerable deviations between bias corrected and observed precipitation (up to 40 mm/month) are still noticeable. Therefore, a consistent application of bias correction in the context of the current impact study, implies that both results achieved with bias corrected and not bias corrected climate inputs are provided as recommended by Ehret et al. (2012), to guarantee that climate change signal is not altered by the bias correction approach under changing conditions. To get a better approximation of the completeness hypothesis, the *TFs* for each climate model were derived using the whole historical climate data available at the reference station (period 1971-2000).

2.4. Hydrological modeling

Observed and RCMs-GCMs based (historical runs and projections) data were used as climate input for the Richards-equation based version 9.05.04 of the Water flow and balance Simulation Model (WaSiM) (Schulla, 2014). WaSiM is a deterministic and spatially distributed model, which uses mainly physically based approaches to describe hydrological processes. The model configuration as applied in this study is shown in Table 2. Schulla (2014) gives more details of the model structure and processes in the Model Description Manual.

A previous study confirmed the suitability of WaSiM to model the hydrology of the Dano catchment. Details of the model setup and parameterization are available in that study (Yira et al., 2016). Briefly summarized, the model was calibrated and validated using observed discharge for the period of 2011-2014, daily time steps and a regular raster-cell size of 90 m. The Latin Hypercube Sampling (*LHS*) was used to identify and optimized sensitive parameters (drainage density, storage coefficient for surface runoff and storage coefficient for interflow) with the Sum of Squared Error set as objective function. Following the *LHS*, several model parametrizations lead to equally good model quality measures. Out of these good parameter sets, the one scoring the highest sum of Pearson product-moment-correlation-coefficient (r^2), Nash Sutcliffe Efficiency (*NSE*, Nash and Sutcliffe, 1970) and Kling-Gupta Efficiency (*KGE*, Gupta et al., 2009; Kling et al., 2012) was used as best parameters set.

In the absence of long term observation discharge for the catchment, the reliability of the model parameters in time could not be assessed in a classical way. Therefore, a soft validation approach was adopted. The approach consisted in determining, based on the Standardized Precipitation Index, whether the calibration/validation years represented normal years in the catchment (considering the historical period of 1990 to 2014). This evaluation showed that both calibration and validation periods are normal and reflect the annual rainfall pattern in the catchment for the period 1990–2014 (Fig.1_ supplementary materials in Yira et al. 2016 shows this evaluation). Therefore, the model parameters for the catchment are expected to be reliable for a long period

In addition to the validation using the discharge, the model was further validated against soil moisture under the dominating soil type and groundwater level recorded by four piezometers. Minimum values of 0.7 for *NSE*, *KGE* and r^2 were achieved during the calibration and validation using observed discharge. r^2 was higher than 0.6 for soil moisture and groundwater level. Therefore, no further model calibration was done in the current study.

Discharge simulated with RCM-GCM historical runs (bias corrected and not bias corrected) were compared to the discharge obtained with observed historical climate data. These comparison runs showed that bias correction was necessary for RCMs-GCMs based simulations to reproduce the historical discharge regime. To integrate the potential effect of bias correction on climate change signal as discussed in section 2.3 and raised by different authors (e.g. Muerth et al., 2013; Ehret et al., 2012; Hagemann et al., 2011), the hydrological model was run with both bias corrected and not bias corrected climate inputs for the climate model ensemble.

No hydrologic observations (discharge, soil moisture and groundwater level) are available for the reference period (1971-2000) in the catchment. The expected climate change for an RCM-GCM is therefore expressed as the relative difference between simulated hydrological variables under reference period (1971-2000) and future period (2021-2050).

2.5. Ecohydrologic analysis

A concept of water-energy budget (Tomer and Schilling, 2009; Milne et al., 2002) was applied to estimate the effectiveness of water and energy use by the catchment as it undergoes climate change. While experiencing climate change, a trend towards the optimization of total unused water-P_{ex} (1) and energy-E_{ex} (2) existing in the environment is usually observed. Plotting P_{ex} against E_{ex} allows for determining the ecohydrologic status of the catchment. The climate change signal can therefore be detected by the shift of this status. The direction of the shift indicates whether the catchment experienced water stress or increased humidity. The approach was used to test its validity in analyzing the interplay between temperature increase and precipitation change as projected by the RCMs-GCMs ensemble.

$$P_{ex} = \frac{(P - ET_a)}{P} \tag{1}$$

$$E_{ex} = \frac{(ET_p - ET_a)}{ET_p} \tag{2}$$

Where P_{ex} is the unused water; E_{ex} is the unused energy; P is the precipitation; ET_a is the actual evapotranspiration; and ET_p is the potential evapotranspiration.

2.6. Assessment criteria

A set of evaluation measures was used to analyze the RCMs-GCMs historical runs, to assess model performance and to estimate the effects of different climate scenarios on hydrological variables:

(i) *P-Factor*, measures the percentage of observed climate data covered by the RCMs-GCMs ensemble historical runs;

(ii) the *R-factor*, calculated following Eq. 3, indicates for an observation series, how wide the range between minimum RCM-GCM and maximum RCM-GCM for precipitation and temperature is, compared to the observation:

$$R - factor\ (Var) = \frac{1}{n\sigma_{Var_{obs}}} \sum_{l=1}^{n} (Var_{Si_{max}} - Var_{Si_{min}}) \tag{4}$$

Where *Var* is the climate variable (e.g. precipitation); n is the observations data points; σ is the standard deviation; *obs* is the observation; Si_{min} is the minimum value of the RCMs-GCMs ensemble; and Si_{max} is the maximum value of the RCMs-GCMs ensemble.

(iii) the normalized root-mean-square deviation (NRMSD), expresses the deviation of each RCM-GCM based precipitation and temperature from the observations;

(iv) the Pearson product-moment-correlation-coefficient (r^2), the percent bias (PBIAS), the Nash Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and the Kling-Gupta Efficiency (KGE) (Gupta et al., 2009; Kling et al., 2012) assess the RCM-GCM based discharge simulations ability to reproduce discharge computed using observed climate data;

(v) change signal (Δ) in climate and hydrological variables (precipitation, temperature and discharge) expresses the difference between projected and historical values (5); and

$$\Delta Var = \frac{\left(Var_{Proj} - Var_{Ref}\right) \times 100}{Var_{Ref}} \tag{5}$$

Where ΔVar is the change signal for the evaluated variable (e.g. discharge); Var_{Proj} is the projected value of the variable (period of 2021-2050 under RCP4.5 and RCP8.5); and Var_{Ref} is the reference value of the variable (period of 1971-2000).

(vi) the Wilcoxon (1945) rank-sum test was used to compare discharge change signal with bias corrected and not bias corrected precipitation data following Muerth et al. (2013). The test evaluated the null hypothesis: "discharge change signal under bias corrected data equals discharge change signal under not bias corrected". The rejection of the test at 5 % implies that future discharge change under bias correction and no bias correction are significantly different. If the test is not rejected, both discharge change under bias correction and change under not bias correction yield the same result, and thus bias correction do not alter the climate change signal on projected discharge.

3. Results

3.1. Historical runs analysis

The comparison between RCM-GCM historical runs and observations for temperature and precipitation is done for the reference period of 1971-2000 for average monthly values. The correlation coefficient is plotted against the *NRMSD* (Fig. 3) for a cross-comparison between RCMs-GCMs in order to assess the relative ability of each RCM-GCM to represent historical climate conditions in the catchment. The correlation coefficient for the RCM-GCM ensemble is in general higher than 0.7 for both precipitation and temperature. The highest coefficients (0.96) are scored by CCLM-ESM for temperature and HIRAM-NorESM for precipitation. The RCMs-GCMs ensemble mean outscores five members of the RCMs-GCMs ensemble with regard to temperature and precipitation (Fig. 3).

The RCMs-GCMs ensemble shows a clear deviation from observed precipitation compared to temperature (Fig. 3). HIRAM-EARTH and CCLM-EARTH present the lowest deviation for temperature and precipitation respectively. The RCMs-GCMs ensemble mean outscores four out of six RCMs-GCMs for temperature and precipitation with regards to the deviation from observed data.

Fig. 4 (A and B) shows a trend towards an overestimation of annual precipitation throughout the reference period for the RCMs-GCMs ensemble when precipitation data are not bias corrected (UC). Although the RCMs-GCMs ensemble presents a large dispersion (*R-factor* = 4.3) only 50 % (*P-factor* = 0.5) of observed precipitation is covered by the RCMs-GCMs ensemble. After bias correction (BC), the RCMs-GCMs ensemble agrees in general with the observed precipitation (*P-factor* = 0.8), moreover the dispersion of climate models based precipitation decreases (*R-factor* = 3.2).

The mean annual precipitation pattern is in general well captured by all RCMs-GCMs (Fig. 4 C and D). However, the climate models ensemble, when not bias corrected, covers only 50 % of monthly precipitation despite a large dispersion (Fig. 4 C). After bias correction, the agreement between RCMs-GCMs based precipitation and observation is considerably improved (Fig. 4 D); and the uncertainty band of the climate model is considerably reduced (*R-factor* = 0.1). However, a slight positive bias is still presented by the climate models ensemble.

Fig. 5 shows that the RCMs-GCMs ensemble fully captures the annual temperature pattern (*P-factor*= 100 %). However, a gap of up to -4 °C between some climate models and observations is noted. This translates into an *R-factor* reaching 8.2. On average, RACMO-EARTH shows an underestimation of temperatures throughout the year, whereas HIRAM-NorESM indicates an opposite trend.

3.2. Climate change signal

The RCMs-GCMs ensemble exhibits a mixed annual precipitation change signal between reference period (1971-2000) and future period (2021-2050) (Table 3). CCLM-CNRM, RAMCO-EARTH and HIRHAM-NorESM project a precipitation increase of about 2.5 to 21 % whereas CCLM-ESM and CCLM-EARTH indicate a decrease of 3 to 11 %. Bias correction has a minor impact on these signals, as the magnitude of projected precipitation increase ranges from 1 to 18 % and the decrease is around 5-13 % after bias correction.

A much more complex intra-annual precipitation change signal is projected by the climate models ensemble (Fig. 6). CCLM-CNRM and HIRHAM-NorESM, which projected an increased annual precipitation, are characterized by an increased rainfall from May to June followed by a decreased rainfall in August. RAMCO-EARTH shows an increased rainfall throughout the season except in July. The decrease in annual precipitation projected by CCLM-ESM and CCLM-EARTH is consistent throughout the entire season. The climate model ensemble consistently projects mean monthly temperature increase of about 0.1 to 2.3 °C under RCP4.5 and 0.6 to 2.5 °C under RCP8.5 leading to an increase of potential evapotranspiration for the climate models ensemble.

3.3. Historical discharge

RCMs-GCMs ensemble based discharges are compared to discharge simulated using observed climate data to evaluate the climate models ability to reproduce the historical discharge regime over the reference period (Fig. 7). Accordingly, performances (*r^2*, *NSE*, *KGE and PBIAS*) achieved by the climate models are presented in Table 4. Fig. 7 (a) shows good agreement between bias corrected climate models based discharge and observation based discharge, with a trend towards discharge overestimation for some climate models (RACMO-EARTH, CCLM-EARTH and HIRAM-EARTH). All climate models show satisfactory statistical quality measures after bias correction. Bias correction impact on simulated historical discharge is shown in Fig. 7 (b). Simulated discharge with not bias corrected data leads to a misrepresentation of the discharge regime (e.g. peak flow is shifted from August to September for CCLM-ESM and discharge is highly overestimated for all climate models). Moreover, poor quality measures are achieved by the climate model ensemble with not bias corrected data (Table 4).

3.4. Discharge change

Projected change in annual discharge for the period of 2021-2050 compared to the reference period is presented in Table 5. Alike for precipitation, a mixed annual discharge change signal is projected by the climate model ensemble. With bias corrected climate data, it is projected: (i) more than 15 % decrease in annual discharge, which is a consequence of relative decrease in precipitation and a consistent increase in potential evapotranspiration for CCLM-ESM, CCLM-EARTH and HIRHAM-EARTH (RCP8.5); and (ii) low to very high (3 to 50 %) increase in total discharge due to increased precipitation not counterbalanced by the evapotranspiration for CCLM-CNRM, RAMCO-EARTH, HIRHAM-NorESM, HIRHAM-EARTH (RCP4.5). This divergence between climate models is reflected through a large amount of uncertainty associated with the projected annual discharge (Fig. 8). The projected intra-annual change in discharge (Fig. 9) is very similar to the precipitation change signal shown in Fig. 6. The discharge changes with not bias corrected climate data are similar in trend (with however differences in magnitude) compared to the changes observed with bias corrected data, which is consistent with changes in the climate signal induced by the bias correction.

The Wilcoxon (1945) rank-sum, testing the significance of the difference between bias corrected and not bias corrected discharge change signal for the climate model ensemble, indicates that the signals are not different at *p-level* equals 0.05. A *p-value* of the Wilcoxon rank-sum test higher than 0.5 is required under both RCP4.5 and RCP8.5 to reject the null hypothesis (H_0: discharge change with bias corrected data = discharge change with not bias corrected data). Hence, the bias correction impact on discharge change signal alteration can be considered negligible.

The sensitivity of the catchment discharge to precipitation and temperature change is tested by plotting, for each member of the climate models ensemble, predicted precipitation and temperature change against predicted discharge change. The result shows that change in total discharge cannot be strongly related to change in potential evapotranspiration (Fig. 10 a). However, a high sensitivity of river discharge to precipitation change (Fig. 10 b) is observed. Under scenario RCP4.5, an increase of +5 % in precipitation leads to an increase of discharge of about

+12.5 %, whereas a decreased precipitation of the same order leads to a decrease of discharge of -13 %. The same simulations under RCP8.5 yield in a +8.3 % discharge increase and a -14.7 % discharge decrease. Interestingly, under RCP8.5 and assuming comparable precipitation between reference and future periods, a discharge decrease of about -3.2 % should be expected (Fig. 10 b).

3.5. Ecohydrologic status

The Ecohydrologic status of the catchment for the reference period and future scenarios RCP4.5 and RCP8.5 is shown in Fig. 11 to illustrate the use of energy and water by the catchment while undergoing temperature increase and precipitation change. Moving left to right along "*Excess water-P_{ex}*" axis indicates that the environmental conditions in the catchment lead to an increase in discharge (CCLM-CNRM, RAMCO-EARTH and HIRHAM-NorESM). Reduction of discharge is experienced when moving the other way round (CCLM-ESM and CCLM-EARTH).

Moving upwards along "*Excess evaporative demand-E_{ex}*" implies drier environmental conditions due to an increase in evaporative demand and soil water deficit. Except for HIRAM-EARTH, all the climate models project drier conditions (increase in *Excess evaporative demand*) under RCP4.5 as a result of an increased temperature not compensated by the amount and/or timing of precipitation. Increased evaporative demand, with marginally aggravated drier conditions, is shown by CCLM-ESM, HIRAM-NorESM, CCLM-EARTH and RCMs-GCMs ensemble mean under RCP8.5.

The ecohydrologic status of the catchment, irrespective of climate model and emission scenario, projects a shift for the period of 2021-2050 compared to the reference period. Therefore, differences in climate conditions between the two periods influence the hydrology (discharge, evapotranspiration, precipitation) of the catchment.

4. Discussion

4.1. Historical runs analysis

All GCMs and RCMs applied in this study have proved in previous works to fairly reproduce the climatology of West Africa (Cook and Vizy, 2006; Dosio et al., 2015; Gbobaniyi et al., 2014; Paeth et al., 2011). The RCMs-GCMs ensemble reasonably captures the annual cycle of temperatures, and following several authors (e.g. Buontempo et al., 2014; Waongo et al., 2015) no bias correction was performed for this climate variable. The systematic positive bias and large deviation from observed precipitation exhibited by the climate models ensemble in this study is also reported by several authors (Nikulin et al., 2012; Paeth et al., 2011) for the southern Sahel Zone. This deviation motivated the bias correction of precipitation. After correction, the positive bias is significantly reduced for all individual climate models and the improvement is clearly visible.

In general, the RCMs-GCMs ensemble mean outperforms individual climate models for both temperature and precipitation. This is due to the fact that individual model errors of opposite sign cancel each other out (Nikulin et al., 2012; Paeth et al., 2011). However, the climate models ensemble mean should not be considered as an expected outcome (Nikulin et al., 2012). Rather considering a large ensemble of climate models should be seen as necessary to properly perform future climate impact studies in the catchment (Gbobaniyi et al., 2014) and to assess the range of potential future hydrological status required for adaptation and management strategies.

4.2. Climate change signal

Compared to the period of 1971-2000, a clear temperature increase signal is projected for 2021-2050 by the six members of the RCMs-GCMs ensemble in the catchment. This feature is common to all multi-model ensemble studies performed in the region (IPCC, 2014). It is further in line with the historical temperature change observed in the region as reported by Waongo (2015) who used the same observation data set applied in the current study. He reported an average +0.31°C/decade and +0.17°C/decade increase for the minimum and maximum temperature respectively for the region considering the period of 1960-2010. However, the climate models ensemble does not agree on the projected precipitation change signal as wetter (RAMCO-EARTH), drier (CCLM-ESM and CCLM-EARTH) as well as mixed (CCLM-CNRM, HIRHAM-NorESM and HIRAM-EARTH) trends are shown by the individual model. It is worth noting that the Dano catchment is located in a region where the "*Coupled Model Intercomparison Project Phase 5 (CMIP5)*" models showed divergent precipitation change for the mid-21st century (IPCC, 2014).

The precipitation change projected by CCLM-CNRM and HIRHAM-NorESM, wetter conditions associated with drought during specific months, is consistent with the change reported by Patricola and Cook (2009) for the West African region. They highlighted an increase in precipitation in general, but also noted drier June and July months. A similar result is achieved by Kunstmann et al. (2008) in the Volta Basin, albeit with a decrease in precipitation at the beginning of rainy season in April.

Precipitation change projected by CCLM-ESM and CCLM-EARTH is consistent with the decrease in June-July-August season noted by Buontempo et al. (2014). A reduction in precipitation during the rainy season is also achieved with RegCM3, driven by ECHAM5 in the Niger River Basin (Oguntunde and Abiodun, 2012). Up to 20.3 % reduction of precipitation in some months is projected, but an increased precipitation during the dry season is also expected.

A critical analysis of CCLM (by Dosio et al., 2015) showed that the model is significantly influenced by the driving GCM (including EC-Earth, ESM-LR, and CNRM-CM). Such an analysis was not found for RACMO and HIRAM. Overestimation of precipitation is a common feature to the RCMs-GCMs ensemble applied in this study, which could suggest that the RCMs inherit the bias from the GCM (Dosio et al., 2015). Consistently with Paeth et al. (2011), the relation between RCM trend and driving GCM cannot be observed in the current study as CCLM-EARTH and RACMO-EARTH clearly show opposite trends although both are driven by EC-EARTH. Differences in projected trends are also highlighted by individual RCMs driven by different GCMs (e.g. CCLM-EARTH and CCLM-CNRM).

4.3. Historical discharge

Compared to the observation based simulation, not bias corrected RCMs-GCMs based discharge is characterized by an overestimation of annual discharge. This misrepresentation results from the positive precipitation bias presented by the climate models ensemble. The bias correction significantly improves the ability of all members of the climate models ensemble to reproduce the historical discharge regime. By comparing simulated discharge with bias corrected and not bias corrected precipitation data, it clearly appears that the bias correction methodology is effective with regards to both discharge regime and total discharge, thus it increases the quality (correspondence between projection and observation) of the model (Murphy, 1993). However, a trend towards discharge overestimation was noticed after bias correction of precipitation. This could be related to:

(i) the relative long period used for the bias correction (1971-2000). As noticed by Piani et al. (2010), fragmenting the correction period to decade and deriving several transfer functions can improve the bias correction result and further contribute to capture the decadal rainfall change that characterizes the West African climate; and

(ii) the fact that temperature was not bias corrected. This led to *ETp* values that vary from one RCM-GCM to another since *ETp* after *Hamon* is computed based on temperature values only (Table 2). As a result, a relatively large range of potential evapotranspiration is observed for the climate models as an ensemble (Table 6).

In view of the general good simulation of historical discharge for the climate models ensemble, it is worth noting that running the hydrological model with simulated climate data of one node at a time (section 2.2) has reasonably bridged the discrepancy between RCMs-GCMs data resolution and hydrological modeling domain (see Fig. 1 of supplementary materials for the hydrological spread of the 9 nodes approach and Fig. 2 of supplementary materials for the difference in precipitation between the 9 nodes approach and the standard 3x3 nodes average approach). Therefore, the approach can be considered as eligible for climate change impact assessment for small scale catchments in which interpolation methods create issues related to the representation of climate variables (particularly precipitation). However, besides regional climate specificities, its reliability might depend on the extent of the RCM-domain used to simulate a given catchment climate, which in the case of this study was set at 0.44°*3 over 0.44°*3 which is the RCM models resolution degraded by a factor of 3. In data available regions, historical RCM-based discharges should necessarily be compared to historical observed discharge, which could not be done in the current study.

4.4. Discharge change

A mixed annual discharge change signal is projected by the climate models ensemble for the period of 2021-2050. These trends agree with several studies in the region (Table 7), although all were carried out at the mesoscale and macroscale:

- ***Negative trend*** (CCLM-ESM and CCLM-EARTH). A discharge decrease of 30 to 46 % is reported by Ruelland et al. (2012) using MadCM3 and MPI-M in the Bani catchment. A similar trend, resulting from a combination of temperature increase and precipitation decrease was reached by Mbaye et al. (2015) using the climate model REMO in the Upper Senegal Basin; as did Cornelissen et al. (2013) and Bossa et al. (2014) in the Térou and the Ouémé catchments in Benin respectively.
- ***Positive trend*** (CCLM-CNRM, RAMCO-EARTH and HIRHAM-NorESM)**.** An increase of 38 % in annual discharge in the region is reported by Ardoin-Bardin et al. (2009) for the Sassandra catchment (South of the Dano catchment) using climate projections of HadCM3-A2. This results from a 11 % increase in precipitation not counterbalanced by the 4.5 % increase of potential evapotranspiration.
- ***Mixed trend*** *(*HIRHAM-EARTH and RCMs-GCMs ensemble). A mixed discharge change signal for the future period is the common signal projected by multi-climate models studies performed in the West African region. In the Niger basin, Aich et al. (2014) simulated change in annual discharge ranging from an increase of up to 50 % to a decrease of up to 50 % using an ensemble of five climate models. Similar signals are reported by Kasei (2009) who applied two climate models (MM5 and REMO) in the Volta basin.

This mixed hydrological change signal is the result of high uncertainties associated to the precipitation change projected by climate models for the catchment (IPCC, 2014). The Wilcoxon rank-sum test further indicated that bias correction did not significantly alter these discharge change signals. Due to the high sensitivity and nonlinear response of the catchment discharge to precipitation, any change in precipitation will have a strong impact on the discharge; the impact will further be pronounced under RCP8.5 compared to RCP4.5. Irrespective of emission scenario, change in potential evapotranspiration alone failed to strongly explain change in annual discharge (Fig. 10 a); this is partly explained by the fact that the environmental system of the catchment is water limited and not energy limited.

The water limited environment of the catchment might also explain the performance of the hydrological model for the climate models ensemble despite the non-bias correction of temperature data (up to 4°C gaps between observed and simulated temperature were noticed for some months, section 3.1). The annual evaporative demand for the climate models ensemble, including RACMO-EARTH which underestimated observed temperature for the reference period, exceeds (almost doubles) precipitation (Table 6). In such a system, also characterized by extended periods with little to no precipitation (November-May) actual evapotranspiration is strongly controlled by precipitation (Guswa, 2005; Schenk and Jackson, 2002). Therefore, an increase in *ETp* is not necessarily translated in an increase in *ETa* as limitation in precipitation (soil moisture) dictates water fluxes (Newman et al., 2006) (e.g. CCLM-EARTH and CCLM-ESM in Table 6).

4.5. Ecohydrologic status

The E_{ex}-P_{ex} plot (Fig. 11) allows accurately displaying climate change impact on the catchment hydrology, as main water balance components (precipitation, discharge and evapotranspiration) are presented in an integrated manner.

The overall ecohydrologic effect of climate change in the catchment, as shown by the plots, is a trend towards drier environmental conditions due to increased evaporative demand-E_{ex}. This denotes an increase in potential evapotranspiration higher than the increase in actual evapotranspiration. By contrast, change in the proportion of precipitation converted to discharge-P_{ex} appears specific to each climate model, with a marginal trend towards discharge increase for the models ensemble under RCP4.5 and discharge decrease under RCP8.5.

All the climate models that project a precipitation increase result in an ETa increase due to the warmer climate. For some of the climate scenarios the projected increase in ETa outperforms the increase in precipitation resulting in a decrease of river discharge (unused water). This indicates that the catchment ecosystem (defined as the vegetation within the catchment and provided by the land use and land cover map of the catchment) is able to optimize the use of water and energy available in the environment, thus reducing unused water (P_{ex}) with temperature increase (Caylor et al., 2009). Such an optimization, although not investigated in this study, may lead plants to change the allocation of fixed carbon to various tissues and organs (Collins and Bras, 2007; Milne et al., 2002). The suitability of the catchment area for the current plant species could also be affected (McClean et al., 2005) by the projected climate change.

In a previous study (Yira et al., 2016), land use in the catchment was found to be characterized by conversion from savannah to cropland implying the reduction of the vegetation covered fraction, root depth, leaf area index etc. Such a land use and land cover change strongly affects the ecohydrologic status of a catchment. Tomer and Schilling (2009) highlighted that removal of perennial vegetation leads to an increase of both *Excess Water*-P_{ex} and *Excess evaporative demand*-E_{ex}. Combining this land use change to climate change impact would therefore on the one hand aggravate water stress for plants in the catchment and on the other hand increase the unused water in the catchment.

5. Conclusion

An ensemble of six RCMs-GCMs data, all produced in the frame of the CORDEX-Africa project, were used as input to a hydrological simulation model to investigate climate change impact on water resources in the Dano catchment by the mid-21st century. The ability of the RCMs-GCMs ensemble to simulate historical climate and discharge was evaluated prior to future climate change impact assessment.

The six climate models fairly reproduce the observed temperature. By contrast, bias correction was necessary for all climate models to accurately reproduce observed precipitation and historical discharge. The applied bias correction method further proved not to alter the discharge change signal. However, projected discharge change signal with and without bias corrected data were tested very comparable. This result indicates that: (i) it is safe to perform bias correction; (ii) bias correction improves the quality of climate models outputs; and (iii) it is not necessary to perform bias correction in order to detect future discharge change signal in the catchment when relative change in climate variables are used as reported by several authors (e.g. Muerth et al., 2013; Hagemann et al., 2011) .

A temperature increase is consistently projected by the models ensemble. This reinforces the commonly acknowledged warming signal for the region. However, the lack of agreement among models with regard to the projected precipitation change signal creates a considerable uncertainty about how the catchment discharge will evolve by 2050. As discharge in the catchment is strongly determined by precipitation, no clear trend in future development of water resources can be concluded due to the high variability of the different climate models and scenarios. Therefore, potential increase and decrease of future discharge have to be considered in climate change adaptation strategies in the region.

The ecohydrological concept as applied in this study proved to fully capture climate change impact on the hydrological conditions within the catchment as both discharge change signal, precipitation and actual/potential evapotranspiration change signal are consistently displayed by the E_{ex}-P_{ex} plot; it further brings insights about the catchment hydro-climatic conditions, which can assist in development of climate change adaptation strategies. The adopted "one node at a time" approach also appears suitable for the assessment of climate change impact on catchment hydrology of small scale catchments. The approach enables the use of climate model input for catchments which are much smaller than the size of one climate model grid cell and, hence, an approximately climate impact analyses for this scale.

The results further underline on the one hand the need for a larger ensemble of projections to properly estimate the impacts of climate change on water resources in the catchment and on the other hand the high uncertainty associated with climate projections for the West African region. Therefore, assessing future climate change impact on water resources for the region needs to be continuously updated with the improvement of climate projections.

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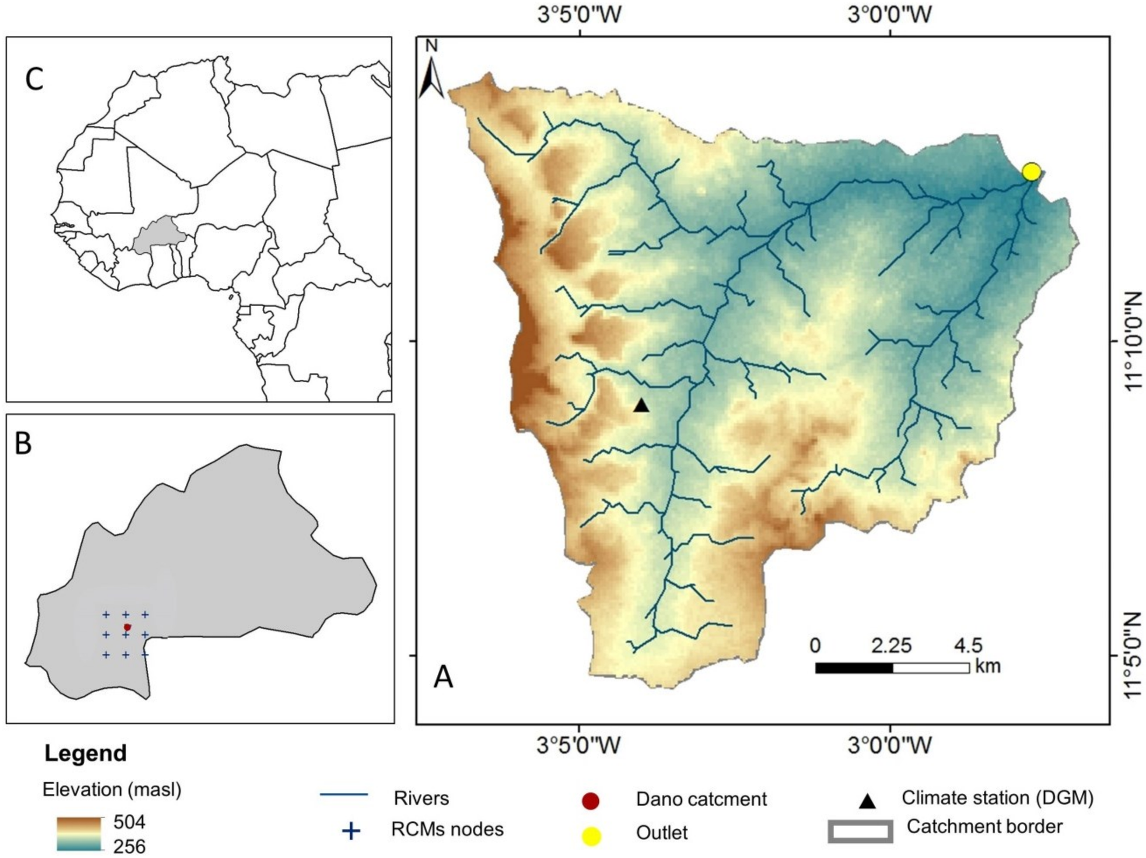


Fig. 1 Location map: (A) Dano catchment, (B) its location in Burkina Faso and (C) in West Africa. (B) RCMs domain used in the study.

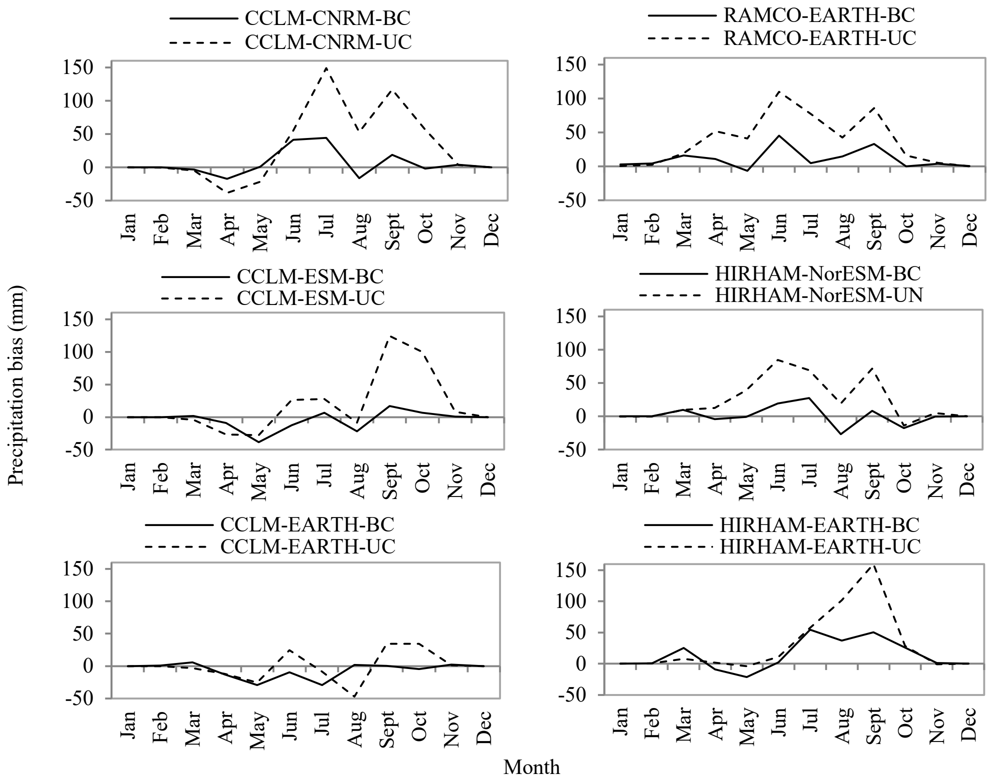


Fig. 2 Absolute precipitation bias (corrected and not corrected) for the model ensemble compared to the observed data for the period of 1991–2000. The transfer functions were calibrated for the period 1971-1990.

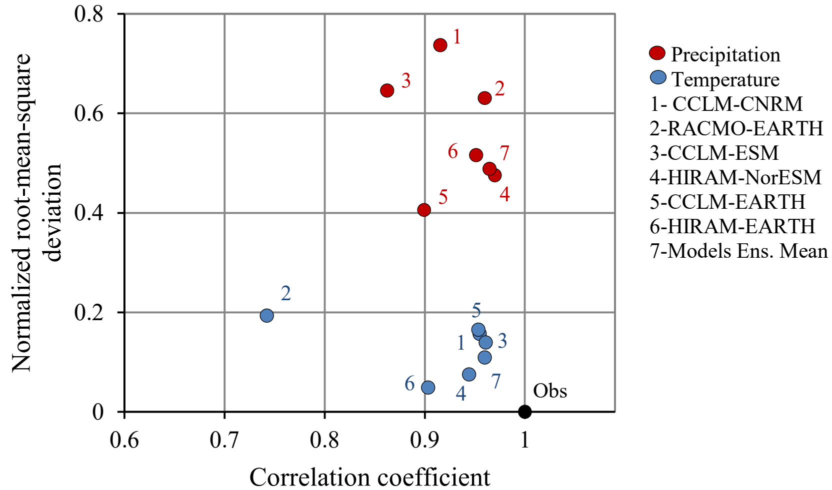


Fig. 3 Statistics of RCM-GCM based precipitation and temperature compared to observations (Obs) for the reference period (1971-2000). Climate model data are not bias corrected. Statistics are computed based on average monthly values.

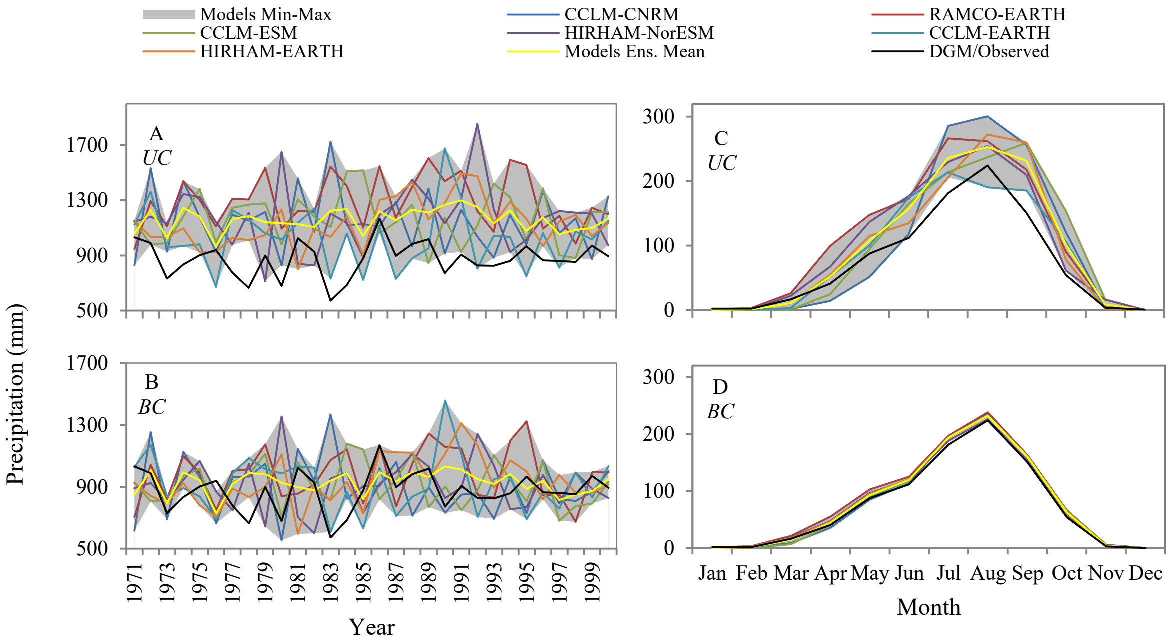


Fig. 4 Historical mean annual (A & B) and mean monthly (C & D) precipitation. *UC* refers to not bias correct, *BC* is bias corrected. *P-factor* equals 50, 80, 50 and 50% for A, B, C and D respectively. *R-factor* equals 4.3, 3.2, 0.6 and 0.11 for A, B, C and D respectively.

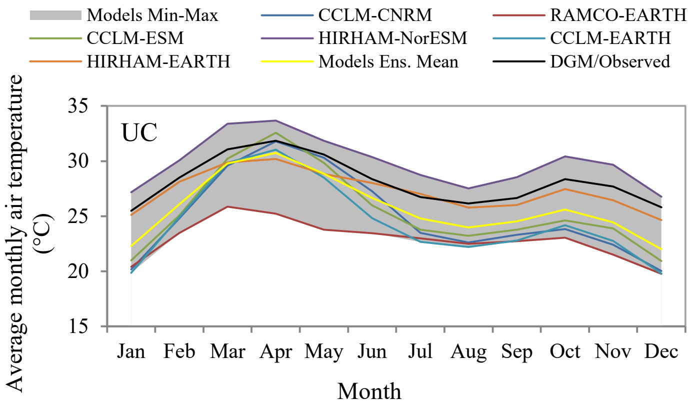


Fig. 5 Monthly air temperature derived from climate models and observations for the reference period (1971-2000). Data are not bias corrected. *P-factor*= 100% and *R-factor*= 8.2.

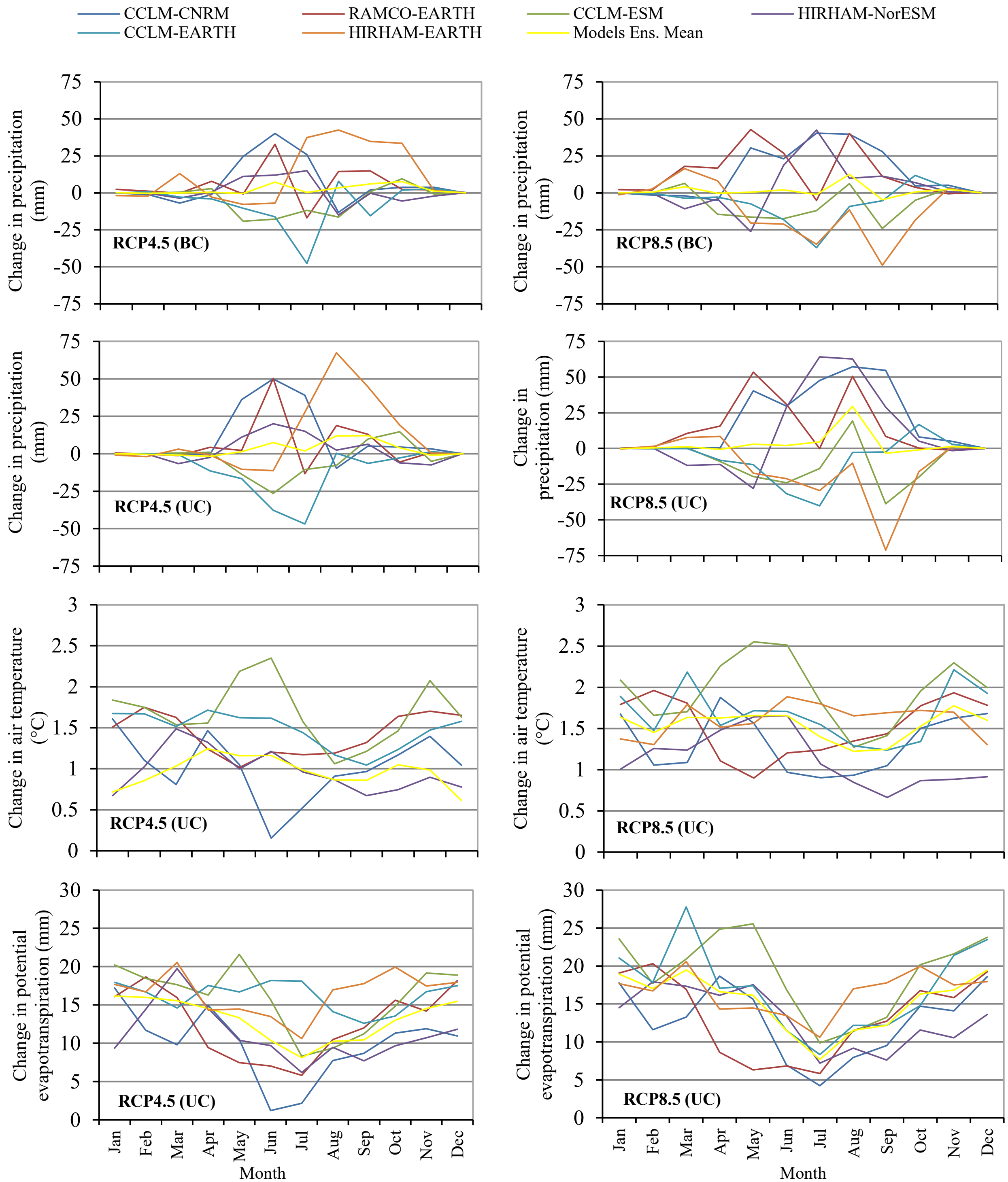


Fig. 6 Climate change signal of precipitation, air temperature and evapotranspiration between the reference (1971-2000) and the future (2021-20150) periods under emission scenarios RCP4.5 and RCP8.5. BC is bias corrected and UC refers to not bias corrected.

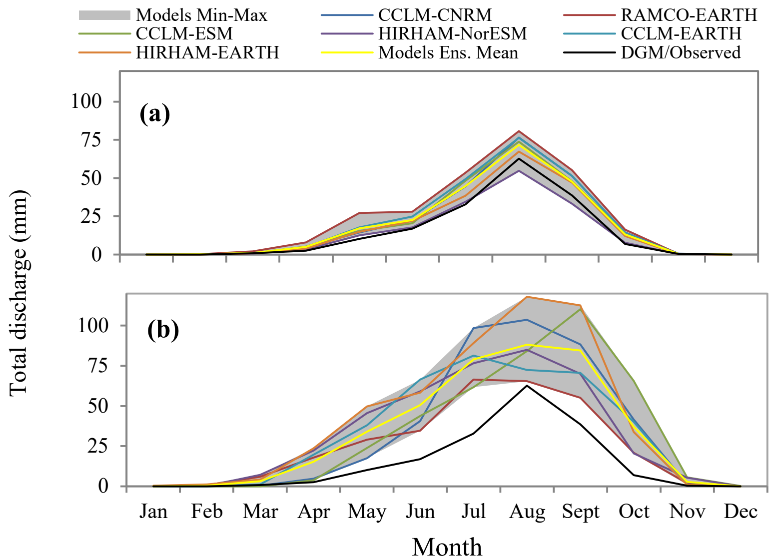


Fig. 7 Historical RCMs-GCMs based discharge simulations and observation based discharge: (a) RCM rainfall are bias corrected, (b) RCM rainfall are not bias corrected.

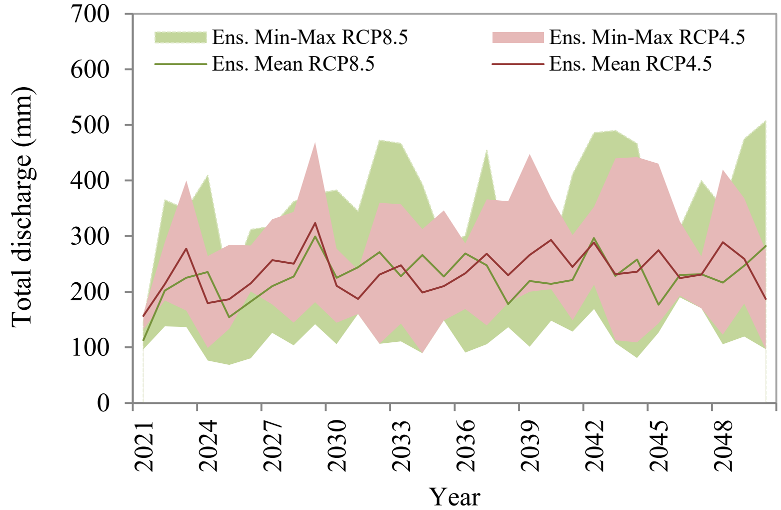


Fig. 8 Projected annual discharge for the climate models ensemble. Simulations are performed with bias corrected precipitation data.

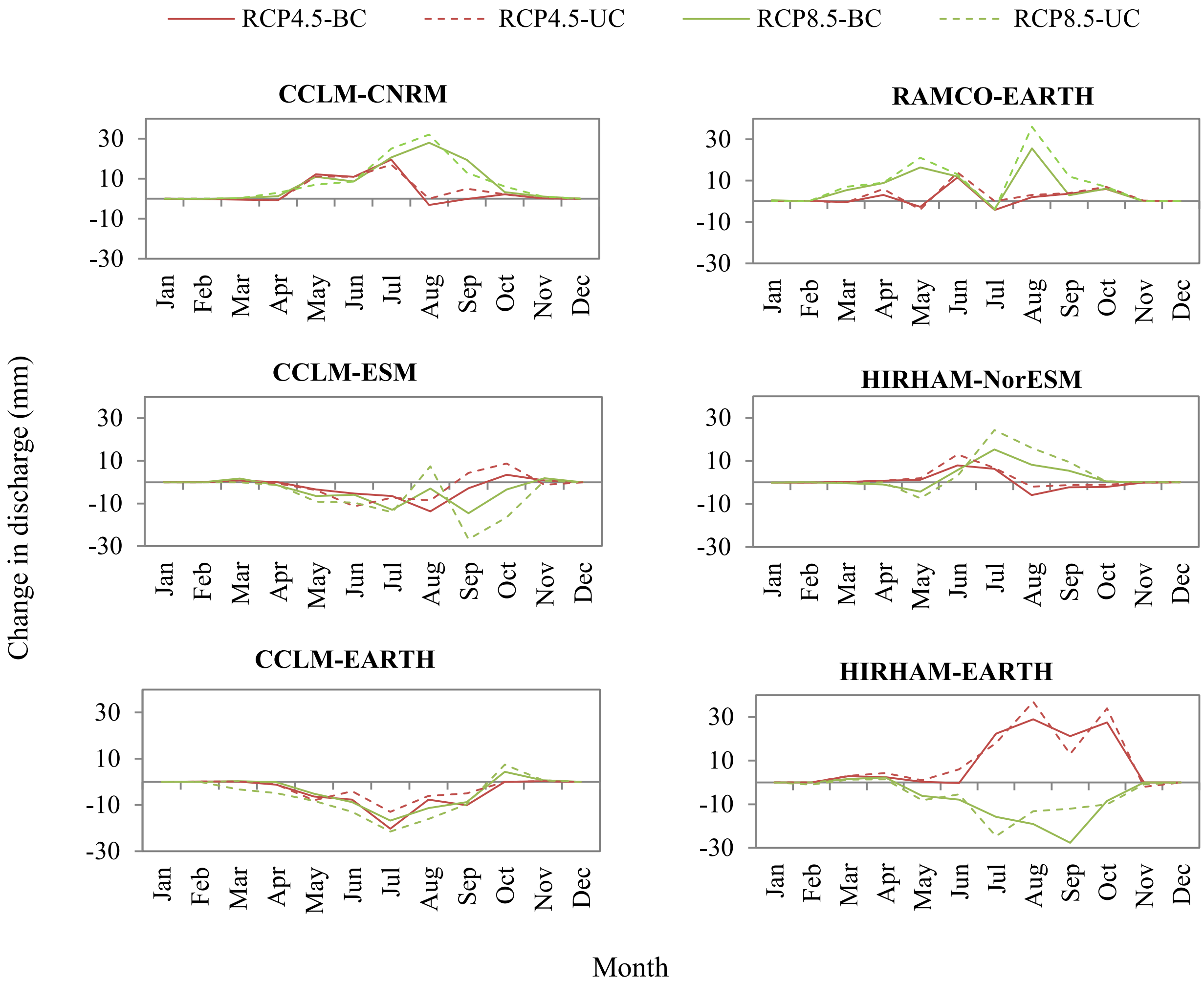
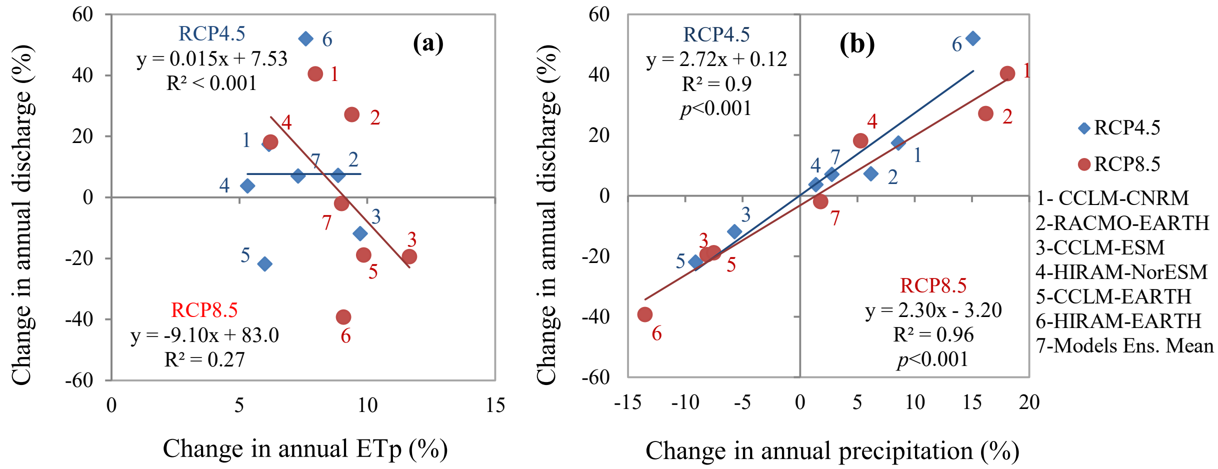


Fig. 9 Monthly discharge change between the reference period (1971-2000) and the future period (2021-20150) under emission scenarios RCP4.5 and RCP8.5. *BC* and *UC* refer to bias corrected and not bias corrected respectively.



725 **Fig. 10** Change in the annual discharge as a response to potential evapotranspiration (a) and precipitation (b) change under emission scenarios RCP4.5 and RCP8.5. Projected precipitation, potential evapotranspiration and discharge changes are calculated comparing period 1971-2000 to period 2021-2050.

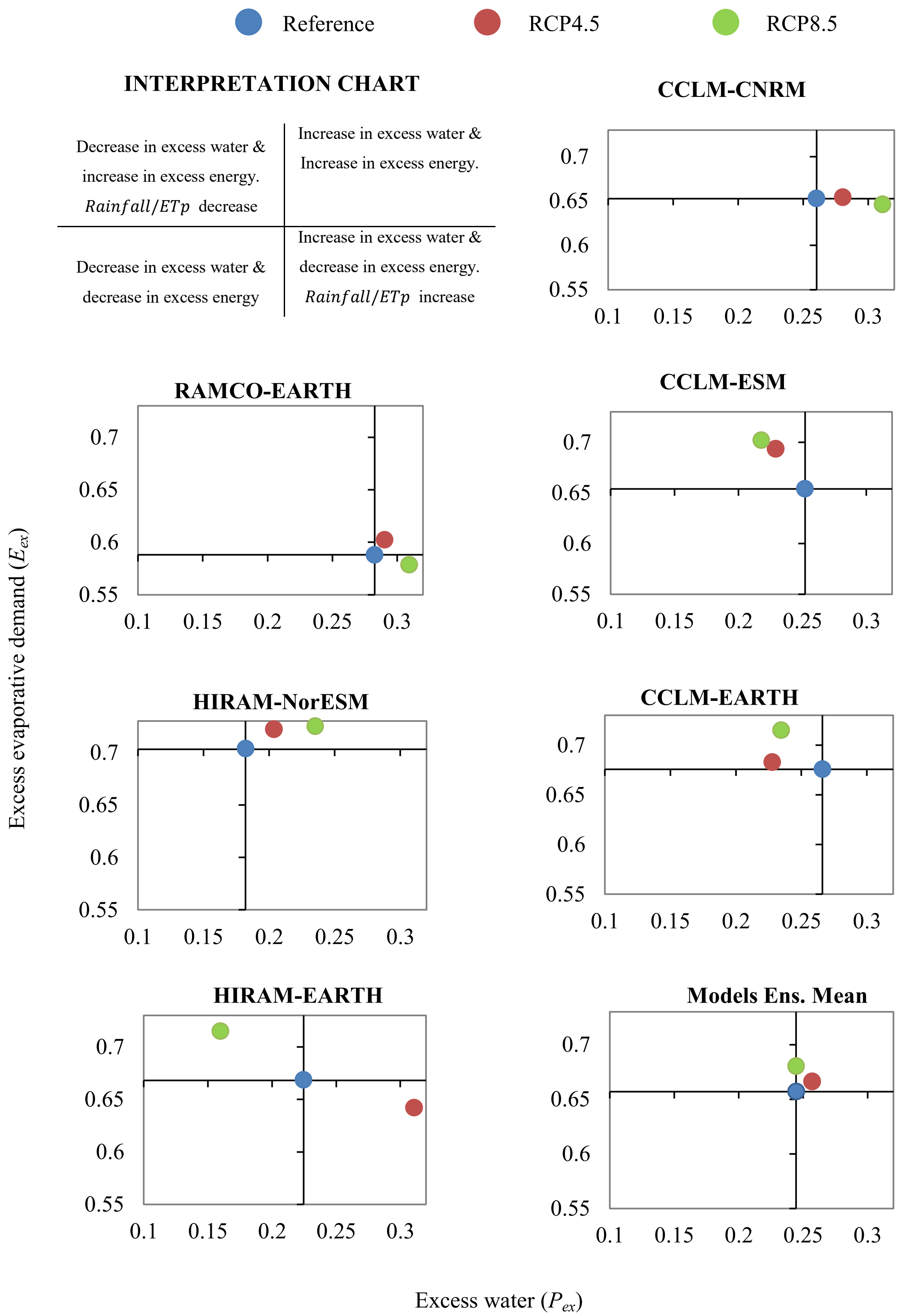


Fig. 11 Plot of excess precipitation (P_{ex}) versus evaporative demand (E_{ex}) for the reference period (1979-2000) and the emission scenarios RCP4.5 and RCP8.5 (2021-2050) for the RCMs-GCMs ensemble. The shift of RCP dots compared to the reference period's dot indicates the effects of climate change on the catchment hydrology. P_{ex} and E_{ex} for each period are calculated from the annual average rainfall, potential evapotranspiration and actual evapotranspiration.

Table 1 RCM-GCM products and corresponding label used in the study

RCM	Driving GCM	RCM Centre/Institute	Label used in the study
CCLM48	CNRM-CM5	CCLMcom	CCLM-CNRM
CCLM48	EC-EARTH	CCLMcom	CCLM-EARTH
CCLM48	ESM-LR	CCLMcom	CCLM-ESM
HIRHAM5	NorESM1-M	DMI	HIRHAM-NorESM
HIRHAM5	EC-EARTH	DMI	HIRHAM-EARTH
RACMO22	EC-EARTH	KNMI	RAMCO-EARTH

Table 2 Selected sub models and algorithms of WaSiM.

Sub model	Algorithm
Potential evapotranspiration	Hamon (based on Federer and Lash, 1983)
Actual evapotranspiration (ET)	Suction depended reduction according to Feddes et al. (1978)
Interception	Leaf area index dependent (bucket approach)
Infiltration	Based on saturated hydraulic conductivity, soil water content and rainfall (Schulla, 2015)
Unsaturated soil zone	Richard’s equation parameterized based on van Genuchten (1980) parameterization of the water retention curve
Discharge routing	Kinematic-wave using Manning-Strickler equation

Table 3 Projected rainfall change between reference (1971-2000) and future (2021-2050) period with bias corrected and not bias corrected RCM-GCM based simulations.

	Not bias corrected			Bias corrected		
RCM-GCM	Historical Precipitation	Precipitation change RCP4.5	Precipitation change RCP8.5	Historical precipitation	Precipitation change RCP4.5	Precipitation change RCP8.5
	(mm)	(%)	(%)	(mm)	(%)	(%)
CCLM-CNRM	1150	+10.9	+21.2	900	+8.9	+18.2
CCLM-EARTH	1027	-11.7	-7.5	918	-9.2	-7.3
CCLM-ESM	1165	-3.3	-9.0	912	-5.7	-8.2
HIRHAM-NorESM	1173	+2.8	+11.7	912	+1.3	+5.5
HIRHAM-EARTH	1135	+12.1	-13.0	934	+15.1	-13.4
RAMCO-EARTH	1292	+5.3	+13.2	979	+6.2	+16.1
Models Ens. Mean	1157	+2.6	+2.8	925	+2.7	+1.8

Table 4 Performance of RCMs-GCMs based discharge compared to observation based discharge. Performance is calculated using mean monthly discharges for the period 1971-2000.

Climate model	r^2	NSE	KGE	PBIAS
		Bias corrected		
CCLM-CNRM	0.99	0.86	0.65	17
CCLM-EARTH	0.97	0.82	0.59	22
CCLM-ESM	0.97	0.87	0.68	14
HIRHAM-NorESM	0.98	0.99	0.92	-1
HIRHAM-EARTH	0.98	0.95	0.78	5
RAMCO-EARTH	0.94	0.65	0.50	27
		Not bias corrected		
CCLM-CNRM	0.88	-1.29	-0.32	100
CCLM-EARTH	0.84	0.43	0.20	50
CCLM-ESM	0.71	-1.41	-0.36	105
HIRHAM-NorESM	0.82	-0.58	-0.32	97
HIRHAM-EARTH	0.71	-0.80	-0.33	97
RAMCO-EARTH	0.89	-2.60	-0.87	148

Table 5 Mean annual discharge change projected by the RCMs-GCMs ensemble for the period 2021-2050 compared to the reference period 1971-2000.

Climate model	Reference discharge	Discharge change RCP4.5	Discharge change RCP8.5
	(mm)	(%)	(%)
Bias corrected			
CCLM-CNRM	232	+16.4	+40.5
CCLM-EARTH	242	-22.7	-19.0
CCLM-ESM	227	-11.9	-18.9
HIRHAM-NorESM	195	+3.6	+17.9
HIRHAM-EARTH	209	+50.7	-39.7
RAMCO-EARTH	273	+6.6	+27.1
Not bias corrected			
CCLM-CNRM	397	+18.4	+39.5
CCLM-EARTH	298	-29.5	-18.5
CCLM-ESM	407	-4.7	-17.2
HIRHAM-NorESM	392	+4.1	+25.8
HIRHAM-EARTH	391	+30.2	-30.9
RAMCO-EARTH	492	+6.7	+24.8

Table 6 Mean annual water balance components per RCM-GCM for the historical (1971-2000) and projected (2021-2050) periods. Precipitation data are bias corrected.

	CCLM-CNRM			CCLM-EARTH			CCLM-ESM			HIRAM-NorESM			HIRAM-EARTH			RACMO-EARTH			OBSERVED
	Bias corrected																		
Water balance components	Historical	RCP4.5	RCP8.5	Historical	RCP4.5	RCP8.5	Historical	RCP4.5	RCP8.5	Historical	RCP4.5	RCP8.5	Historical	RCP4.5	RCP8.5	Historical	RCP4.5	RCP8.5	Historical
Precipitation (mm/y)	900	980	1064	918	834	851	912	860	837	912	924	962	934	1075	809	979	1040	1137	898
Potential *ET* (mm/y)	1992	2110	2143	1917	2111	2132	1977	2169	2206	2215	2349	2371	2052	2249	2252	1703	1853	1863	2070
Actual *ET* (mm/y)	667	706	733	674	644	651	684	665	656	746	754	765	725	742	679	703	738	785	703
Total discharge (mm/y)	232	270	326	242	187	196	227	200	184	195	202	230	209	315	126	273	291	347	198
Surface runoff (mm/y)	103	141	171	111	78	84	100	91	78	81	86	106	89	175	49	136	153	195	92.9
Interflow (mm/y)	116	118	143	117	100	103	115	100	97	104	110	82	109	129	71	125	126	137	98.0
Baseflow (mm/y)	13	12	13	12	12	12	12	10	11	12	11	10	13	12	12	14	14	16	8.9
	Not bias corrected																		
Precipitation (mm/y)	1150.4	1276	1394	1027	907	950	1165	1127	1060	1173	1206	1310	1135	1272	987	1292	1361	1462	898
Potential *ET* (mm/y)	1992	2110	2143	1917	2111	2132	1977	2169	2206	2215	2349	2371	2052	2249	2252	1703	1853	1863	2070
Actual *ET* (mm/y)	753	806	840	729	697	707	758	740	723	781	798	817	744	763	717	801	833	849	703
Total discharge (mm/y)	397	470	554	298	210	243	407	387	337	392	408	493	391	509	270	491	524	613	198
Surface runoff (mm/y)	166	223	266	134	83	98	152	141	119	170	178	185	173	227	122	256	269	289	92.9
Interflow (mm/y)	204	216	255	146	113	129	224	217	192	196	201	267	185	228	129	201	217	267	98.0
Baseflow (mm/y)	27	31	37	18	14	16	31	29	26	26	29	41	33	54	19	34	38	57	8.9

Table 7 Selected studies of climate impact on water resources in the West African Region

Study	Location/seize	GCM/RCM	Scenario	Reference period	Future period	Precipitation change (%)	Discharge change (%)
Ruelland et al. (2012)	Bani catchment, Mali/100 000Km²	MadCM3 and MPI-M	A2	1961-1990	2041-2070	-2 to -10	-30 to -46
Mbaye et al. (2015)	Upper Senegal Basin, Senegal-Mali-Mauritania/218000 Km²	REMO-MPI-ESM-LR	RCP4.5 and RCP8.5	1971-2000	2071-2100	negative trend	up to -80
Aich et al.(2014)	Niger Basin/ 2156000 Km²	HadGEM2-ES, IPSL-5 CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M, NorESM1-M	RCP8.5	1970-1999	2070-2099	mixed trend	-50 to +50
Ardoin-Bardin et al. (2009)	Sassandra, Ivory Coast/ 62173 Km²	HadCM3-A2	-	1971-1995	2036-2065	11.4	38
Bossa et al. (2014)	Ouémé catchment, Benin/ 49256 Km²	REMO-ECHAM5/MPI-OM	A1B	2000-2009	2010-2029	-10	-18
Cornelissen et al. (2013)	Térou Catchment, Benin/2344 km²	REMO-ECHAM5/MPI-OM	B1	2001-2010	2031-2049	-11	-11
Kasei (2009)	Volta Basin/400000 km²	MM5 and REMO	B1	1991-2000 and 1961-2000	2030-2039 and 2001-2050	+12 and -6	+40 and -5